

A Tableau-Based Business Intelligence Dashboard for Multidimensional Analysis of Natural Disaster Impacts in Indonesia

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ABSTRACT

Indonesia is highly vulnerable to natural disasters and generates large volumes of disaster data each year. However, this information is still presented predominantly in tabular reports, which limits multidimensional analysis and weakens its value for evidence-based decision-making. Existing studies emphasize descriptive visualization without integrating a data warehouse architecture to support comprehensive disaster analytics. This study therefore develops a Tableau-based Business Intelligence dashboard supported by a data warehouse for multidimensional analysis and forecasting of natural disaster impacts in Indonesia. The data warehouse was designed using Ralph Kimball's Nine-Step Methodology, and the Extract, Transform, Load (ETL) process was implemented in Pentaho Data Integration. The dataset comprises 21,986 disaster events recorded by the National Disaster Management Agency (BNPB) from January 2021 to September 2025. The dashboard provides interactive visualizations of disaster trends, regional distribution, casualties, damage levels, and the ten provinces with the highest recorded impacts, together with forecasting based on Tableau's exponential smoothing (ETS) model. The analysis identified West Java as the province with the highest recorded disaster impacts in absolute terms during the study period. The resulting platform integrates data warehousing, multidimensional visualization, and forecasting to support disaster mitigation and response planning.

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1. Introduction

Indonesia is one of the countries most vulnerable to natural disasters because of its location at the convergence of the Eurasian, Indo-Australian, Pacific, and Philippine tectonic plates [1]. Consequently, the country frequently experiences earthquakes, tsunamis, volcanic eruptions, floods, landslides, droughts, extreme weather, and forest and land fires [2]. In addition to geological hazards, climate change has intensified the frequency and severity of hydrometeorological disasters, increasing their impacts on communities, infrastructure, and the environment [3]. According to the National Disaster Management Agency (BNPB), Indonesia recorded 21,986 disaster events between January 2021 and September 2025, resulting in numerous casualties and extensive damage to residential buildings and public facilities [4]. As disaster records continue to increase, effective management and analysis of historical disaster data have become essential to support disaster mitigation, preparedness, response, and policy formulation [5].

Although BNPB provides public access to disaster data, the information is predominantly presented in tabular reports, making it difficult to efficiently identify disaster trends, compare regional impacts, and analyze casualties and damage across multiple dimensions [6]. Such limitations reduce the effectiveness of disaster information for supporting timely and evidence-based decision-making. Business Intelligence (BI) offers capabilities for integrating historical data, performing multidimensional analysis, and presenting analytical results through interactive dashboards [7], [8]. Supported by a data warehouse, BI enables users to explore data from different perspectives and transform large volumes of historical records into meaningful information for decision support [9], [10], [11].

Previous studies have demonstrated the application of BI technologies in disaster-related domains. Lessy et al. employed tableau to analyze earthquake data [12]. Irwan and Trisnawarman implemented a Power BI dashboard for earthquake and tsunami monitoring [13]. Abdillah et al. applied BI techniques to analyze national mortality data [14]. These studies confirm the usefulness of BI dashboards for disaster information management. However, they mainly focus on specific disaster types or descriptive visualization and provide limited support for integrated multidimensional analysis of disaster impacts across temporal, spatial, disaster-type, casualty, and damage dimensions. Furthermore, forecasting capabilities are rarely incorporated into an integrated analytical platform to support disaster management decision-making.

Based on these limitations, this study proposes a tableau-based Business Intelligence framework supported by a Kimball-based data warehouse and ETL processes using Pentaho Data Integration. The framework integrates historical disaster records from January 2021 to September 2025 into a unified analytical environment and provides interactive visualizations, geographic mapping, dynamic filtering, and disaster impact forecasting using tableau's built-in Exponential Smoothing (ETS) model. By integrating data warehousing, multidimensional analytics, and forecasting within a single platform, this study enhances the analytical capability of disaster data beyond conventional tabular reporting and provides evidence-based insights to support disaster mitigation and response.

2. Research Methodology

This study employed a design and development research approach to develop a Business Intelligence framework for multidimensional analysis and forecasting of natural disaster impacts in Indonesia. The framework integrates data collection, data preprocessing, data warehouse design, ETL implementation, dashboard development, forecasting, and dashboard analysis. The overall research workflow is illustrated in figure 1.

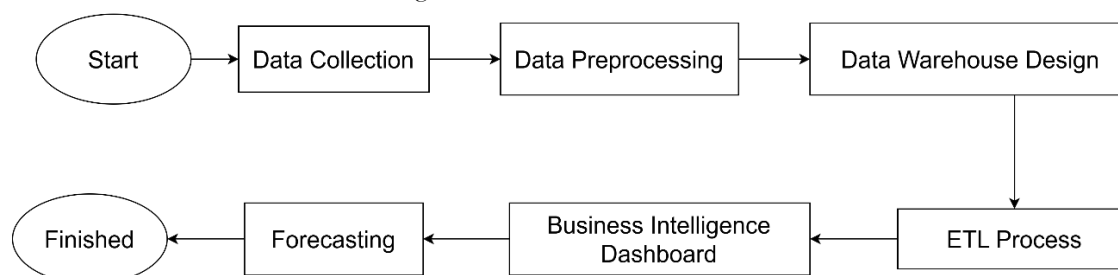


Figure 1. Research Flowchart

2.1 Data Collection

The dataset used in this study consists of historical natural disaster data obtained from the official website of the National Disaster Management Agency (BNPB). The dataset covers the period from January 2021 to September 2025 and contains 21,986 disaster events across Indonesia. Each record includes information on the disaster date, disaster type, province, district, casualties (fatalities, injuries, and missing persons), and infrastructure damage, including damaged houses, flooded houses, and damaged public facilities. These historical records provide the basis for multidimensional analysis of disaster impacts through a Business Intelligence dashboard.

2.2 Data Preprocessing

Before the ETL process, the dataset underwent preprocessing using Pentaho Data Integration. This stage included removing duplicate records, handling missing values, standardizing province names, district names, and disaster categories, and converting data into appropriate formats for data warehouse integration. These preprocessing procedures were performed to improve data consistency and ensure that the integrated dataset could be reliably analyzed through the Business Intelligence dashboard.

2.3 Data Warehouse Design

The data warehouse was designed using the Nine-Step Methodology introduced by Ralph Kimball, as applied in recent studies [15]. This methodology was selected because it provides a systematic approach for designing dimensional data warehouses that support analytical processing and Business Intelligence applications. The resulting star schema integrates historical disaster data into a centralized repository to facilitate multidimensional analysis and improve query performance.

The implementation of the Nine-Step Methodology consists of the following stages.

a. Choose the Process

The first step involves identifying the business process to be analyzed in this study. The selected business process is the analysis of natural disaster data in Indonesia based on disaster type, location of the incident, time, and the impact of the disaster in terms of casualties and damage. The selection of this process aims to produce a Business Intelligence dashboard capable of displaying information interactively, thereby making it easier for users to understand disaster conditions in Indonesia.

b. Choose the Grain

This stage is conducted to determine the level of data detail to be stored in the fact table. The “grain” is defined based on each disaster event occurring at a specific time and location. Each data record represents a single disaster event containing information on the date of the event, province, type of disaster, number of casualties, and extent of damage. Determining the grain is crucial because it influences the structure of the fact table and the level of detail in the dashboard analysis.

c. Identify and Define the Dimensions

This stage involves identifying the dimension tables used in the data warehouse. Based on the dashboard's requirements, this study uses several dimension tables, namely the time dimension, location dimension, and disaster dimension, as shown in table 1.

Table 1. Dimension Tables

No	Dimension Table	Description
1	dim_waktu	Dimensions based on the time of the disaster

2	dim_lokasi	Dimension based on the region where the disaster occurred
3	dim_bencana	Dimension based on disaster category

d. Choose the Fact

This step is performed to determine the fact table used in the data warehouse. The fact table used is fact_bencana, which contains key numerical data such as fatalities, missing persons, injuries, damaged homes, flooded homes, and damaged public facilities.

e. Store Pre-Calculations in the Fact Table

This step is performed to determine the calculation results stored in the fact table. In this study, there are several aggregated data points used to support the dashboard analysis process, such as total casualties and total damage.

f. Round Out the Dimensions Table

This stage involves completing the attributes in each of the designed dimension tables. These attributes are tailored to the needs of disaster data analysis and will be used as references in the fact table. The attribute structures for each dimension table are shown in table 2.

Table 2. Attributes of the Dimension Tables

No	Dimension	Attribute	Description
1	dim_waktu	waktu_id	Primary key generated by PostgreSQL as an auto-increment, not null
		tanggal	Not null
		tahun	Not null
		bulan	Not null
		nama_bulan	Not null
2	dim_lokasi	lokasi_id	Primary key generated by PostgreSQL as an auto-increment, not null
		provinsi	Not null
		kabupaten	Not null
3	dim_bencana	bencana_id	Primary key generated by PostgreSQL as an auto-increment, not null
		kejadian	Not null

g. Choose the Database Duration

This step is performed to determine the time range of the data used in the study. In this study, the data used is a dataset on natural disasters in Indonesia from January 2021 to September 2025.

h. Track Slowly Changing Dimensions

This step is performed to determine how to manage data changes in the dimension tables. In this study, changes in dimension data are relatively minor, so Type 1 Slowly Changing Dimensions (SCD) are used. This is done by updating old data with the latest data without storing the history of previous changes. Additionally, the study focuses more on analyzing current data rather than storing the history of changes in dimension data.

i. Determine Query Priorities and Query Modes

The final stage involves determining query priorities and data access requirements for the dashboard. The data warehouse is designed to support analytical queries on the Business Intelligence dashboard using tableau, allowing users to filter data, drill down by region, analyze time trends, and assess the impact of disasters interactively. The star schema structure used helps improve query performance and simplifies the data visualization process on the Business Intelligence dashboard.

2.4 ETL Process

The Extract, Transform, Load (ETL) process was implemented using Pentaho Data Integration. During the extract stage, historical disaster data were retrieved from the BNPB dataset. The transform stage standardized data structures according to the dimensional model and applied preprocessing results. Finally, the transformed data were loaded into PostgreSQL, including both fact and dimension tables, to establish the data warehouse.

2.5 Business Intelligence Dashboard Development

The Business Intelligence dashboard was developed using tableau to present interactive visualizations of disaster data. The dashboard includes cards visualization, geographic distribution maps, bar charts, trend charts, and interactive filters based on year, province, and disaster type.

In addition, the dashboard provides a “Pilih Dampak” parameter that enables users to dynamically select the disaster impact category for analysis. The available categories include casualties, represented by fatalities, injuries, and missing persons, and damage, represented by damaged houses, flooded houses, and damaged public facilities. All dashboard visualizations are automatically updated according to the selected impact category, enabling flexible multidimensional analysis.

2.6 Forecasting Method

Disaster impact forecasting was performed using tableau’s built-in forecasting functionality, which implements the Exponential Smoothing (ETS) model. Monthly disaster impact data from January 2021 to August 2025 were used as the input time series, while September 2025 was generated as the forecast period. tableau automatically selected the most appropriate ETS model based on the characteristics of the historical data without requiring manual parameter configuration.

The forecasting process was integrated with the “Pilih Dampak” parameter, allowing users to dynamically forecast either casualty indicators or damage indicators. Forecast performance was evaluated using the quality metrics automatically generated by tableau, including Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Scaled Error (MASE), and Mean Absolute Percentage Error (MAPE). The forecasting results are intended to provide exploratory trend projections that support disaster impact analysis within the dashboard.

3. Results and Discussion

3.1 Data Preprocessing Results

The data preprocessing stage produced a cleaned and standardized disaster dataset that was ready for subsequent data warehouse implementation. Using Pentaho Data Integration, preprocessing consisted of duplicate record removal, missing value handling, attribute selection, standardization of province names, regency/city names, and disaster categories, as well as data type conversion before loading the data into the PostgreSQL data warehouse. These processes ensured that the dataset was consistent and suitable for multidimensional analysis through the Business Intelligence dashboard. The preprocessing workflow is presented in figure 2.

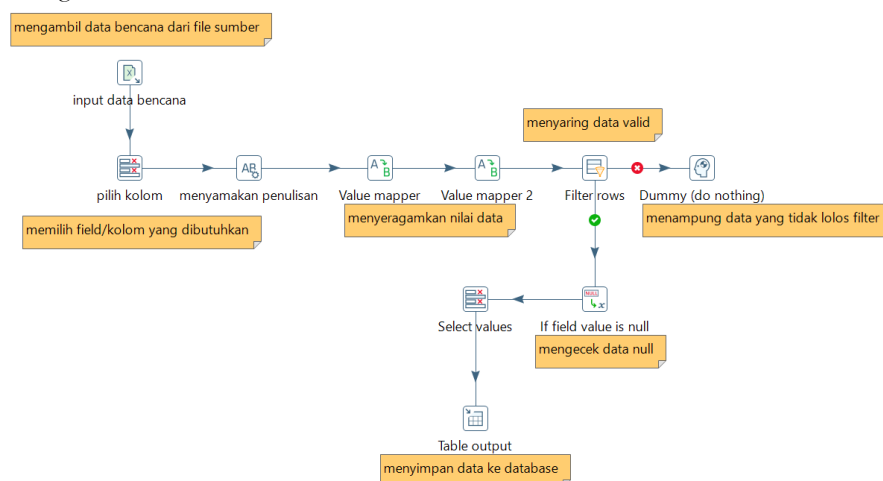


Figure 2. Data Preprocessing

The preprocessing stage resulted in a dataset containing ten main attributes that represent the essential information required for disaster analysis, including the disaster date, disaster type, location, casualty indicators, and infrastructure damage. These attributes were retained because they provide the minimum information necessary for dimensional modeling and support interactive analysis in the Business Intelligence dashboard. The metadata of the processed dataset is presented in table 3.

Table 3. Metadata from Preprocessing

No	Attribute Name	Data Type	Description
1	tanggal_kejadian	Date	The date the disaster occurred, normalized to a date format
2	kejadian	Varchar	The type of disaster that has been cleaned and standardized
3	kabupaten	Varchar	The names of regencies/cities that have been standardized
4	provinsi	Varchar	Standardized province name
5	korban_meninggal	Integer	Number of fatalities
6	korban_hilang	Integer	Number of missing persons
7	korban_terluka	Integer	Number of injured victims
8	rumah_rusak	Integer	Number of damaged houses
9	rumah_terendam	Integer	Number of homes flooded as a result of the disaster
10	fasum_rusak	Integer	Number of public facilities that sustained damage

The preprocessing process contributes to improving data consistency before the ETL stage by reducing data redundancy and standardizing attribute values. Consistent data are particularly important for multidimensional analysis because inconsistent administrative names or disaster categories may lead to inaccurate aggregation and visualization results. By producing a standardized dataset, the ETL process can integrate disaster information into the data warehouse more efficiently and provide reliable data for dashboard visualization. Data preprocessing is therefore a critical step in improving the quality of analytical results and supporting effective decision-making.

3.2 Results of the ETL Process in the Data Warehouse

a. Star Schema

The data warehouse design utilizes a star schema model consisting of one fact table, namely fact_bencana, and three dimension tables: dim_bencana, dim_lokasi, and dim_waktu. The fact table is at the center of the schema and is connected to the dimension tables via foreign keys. The fact table is used to store primary data related to the impact of disasters, such as the number of fatalities, missing persons, injured victims, damaged homes, flooded homes, damaged public facilities, total number

of victims, and total damage. Meanwhile, the dimension tables are used to provide supporting information in the form of disaster type, incident location, and time of occurrence, as shown in figure 3.

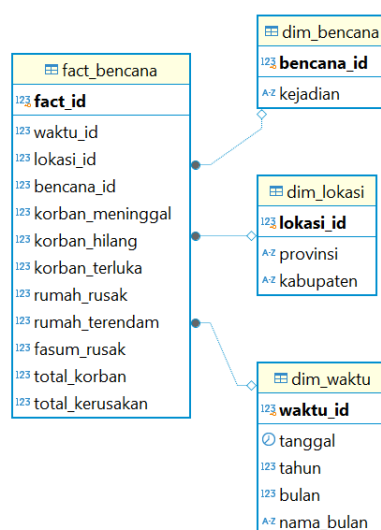


Figure 3. Star Schema of a Data Warehouse

The star schema provides an efficient dimensional structure for analytical processing by separating descriptive information from quantitative disaster measures. This design simplifies multidimensional queries and improves dashboard performance, allowing disaster impacts to be analyzed by time, location, and disaster type more effectively.

b. Dimension Tables

The dim_bencana table was created to store disaster category information as descriptive data that supports analysis on the Business Intelligence dashboard. This table consists of the bencana_id attribute as the primary key and the kejadian attribute, which represents the type of disaster. The table creation process was carried out through ETL stages using Pentaho Data Integration so that each disaster category was successfully integrated into the data warehouse consistently without data duplication. The results of the transformation to create the dim_bencana table are shown in figure 4. The implementation of the dim_bencana table ensures that disaster categories are stored consistently in the data warehouse. Standardized disaster classifications reduce data redundancy and improve the reliability of disaster aggregation across different analyses.

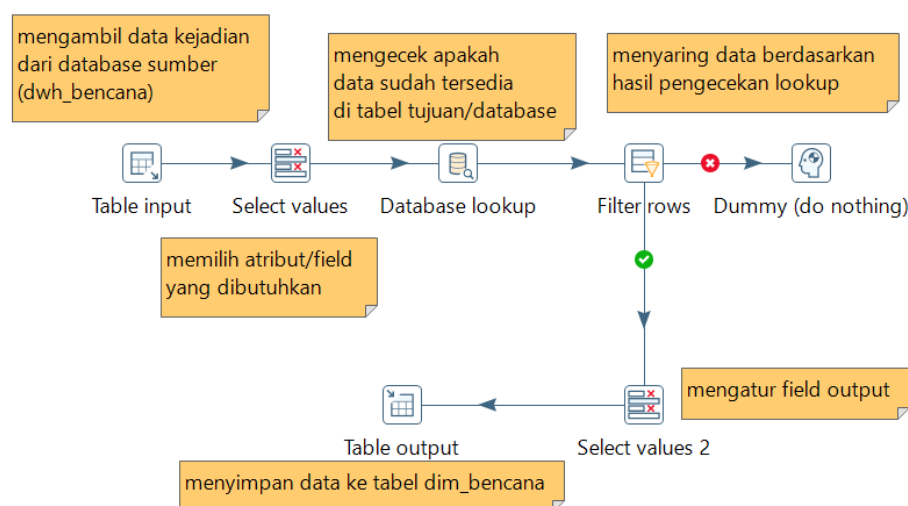


Figure 4. Disaster Dimension ETL Process

The dim_lokasi table was created to store information on the locations of disaster events based on province and regency/city as descriptive data in the data warehouse. This table consists of the lokasi_id attribute as the primary key, along with the provinsi and kabupaten attributes. The ETL process using Pentaho Data Integration successfully integrated location data into the dim_lokasi table consistently while avoiding data duplication. The results of the dim_lokasi table creation are shown in figure 5. The dim_lokasi table supports geographical analysis by providing standardized province and regency information. This implementation improves the accuracy of spatial visualization and enables consistent regional comparisons within the dashboard.

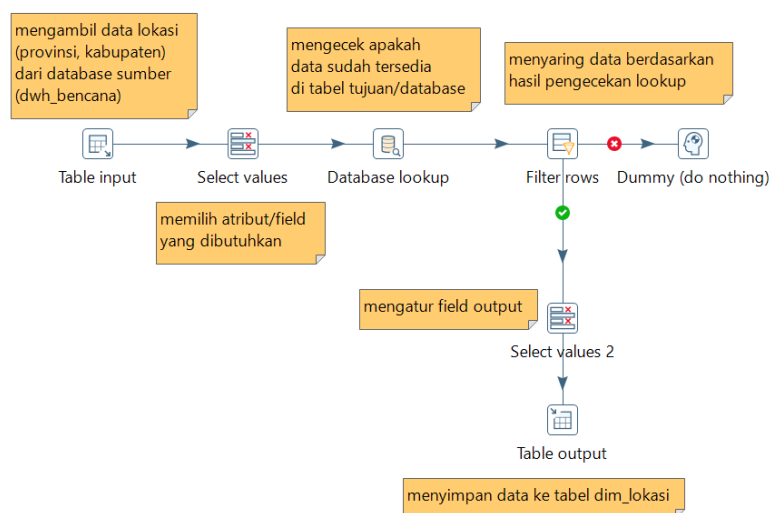


Figure 5. Location Dimension ETL Process

The `dim_waktu` table was created to store information on the timing of disaster events as the basis for temporal analysis on the Business Intelligence dashboard. This table consists of the `waktu_id` attribute as the primary key, along with `tanggal`, `tahun`, `bulan`, and `nama_bulan`. The ETL process using Pentaho Data Integration successfully integrated the time data into the `dim_waktu` table consistently while avoiding data duplication, thereby supporting disaster trend analysis based on time periods. The results of the transformation to create the `dim_waktu` table are shown in figure 6. The `dim_waktu` table organizes disaster events into temporal dimensions, allowing users to analyze historical trends and seasonal patterns. This structure also provides the temporal basis required for forecasting analysis in tableau.

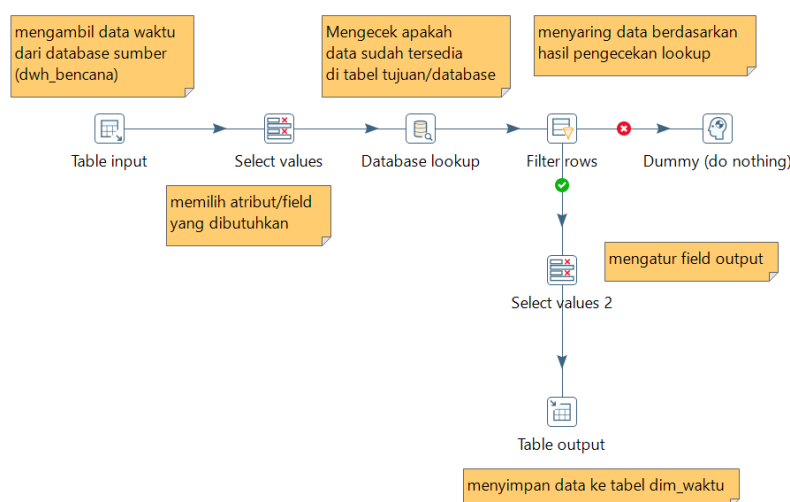


Figure 6. Time Dimension ETL Process

c. Fact Table

The `fact_bencana` table was built as a central repository for numerical data to support analysis on the Business Intelligence dashboard. This table links the `dim_waktu`, `dim_lokasi`, and `dim_bencana` tables via foreign key attributes and stores data on fatalities, missing persons, injuries, damaged homes, flooded homes, damaged public facilities, `total_korban`, and `total_kerusakan`. The ETL process using Pentaho Data Integration successfully integrated data from all dimension tables and created a fact table ready for multidimensional analysis. Additionally, the `total_korban` and `total_kerusakan` values were calculated during the transformation process to improve query efficiency and visualization on the dashboard. The results of the transformation to create the `fact_bencana` table are shown in figure 7. The `fact_bencana` table centralizes quantitative disaster measures into a single analytical table. This implementation reduces query complexity and improves dashboard response time by enabling efficient aggregation of disaster impact indicators.

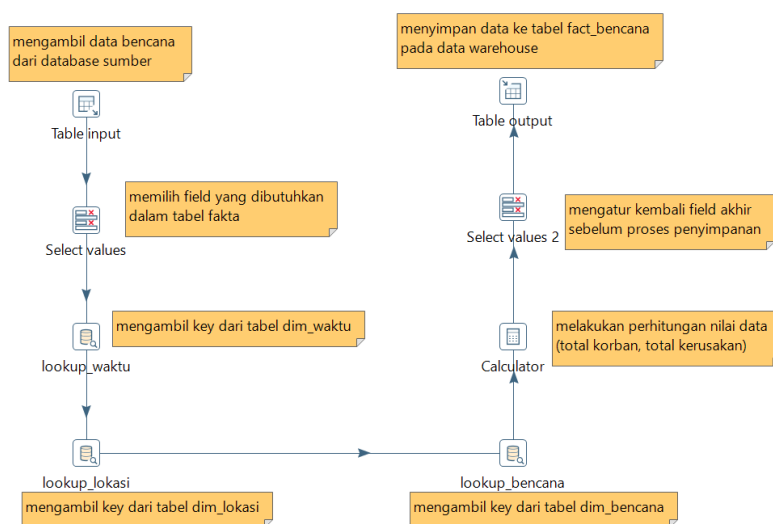


Figure 7. Fact Table ETL Process

d. Dashboard Data Mart

After the fact table and dimension tables were successfully built, a data mart was created as the data source for the Business Intelligence dashboard. This process integrated the fact_bencana table with the dim_waktu, dim_lokasi, and dim_bencana tables through an ETL process using Pentaho Data Integration. The integration resulted in a dataset containing information on time, location, disaster type, and impact data within a single structure ready for visualization. The datamart was then exported to Microsoft Excel as a data source for tableau. The integrated data structure enables faster visualization and supports interactive data analysis. The result of the data mart creation is shown in figure 8.

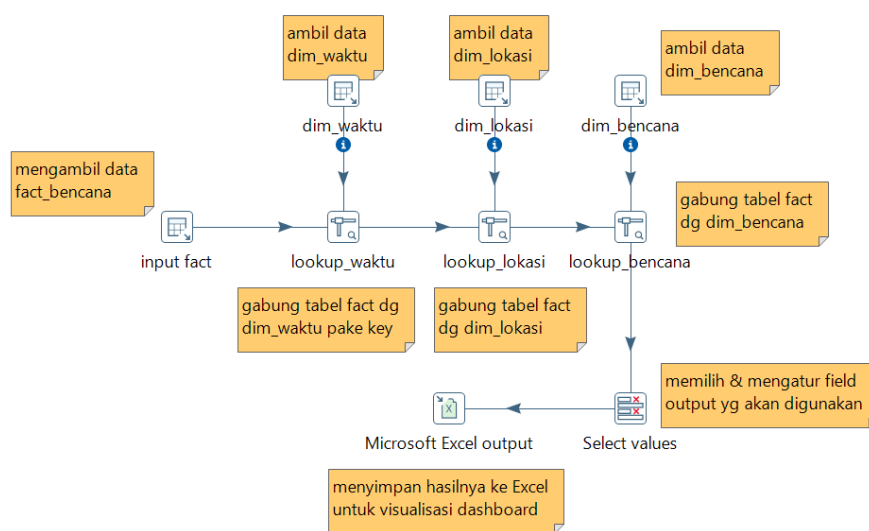


Figure 8. Data Mart Transformation Process for the Dashboard

The dashboard data mart integrates fact and dimension tables into a unified analytical dataset that serves as the primary data source for tableau. This integration improves data retrieval efficiency and supports interactive filtering, drill-down analysis, and multidimensional exploration of disaster information.

3.3 Business Intelligence Dashboard Results

The dashboard was created using the tableau application with data sourced from the disaster datamart resulting from the ETL process and data warehouse design. The dashboard is designed to interactively display information regarding trends, regional distribution, the impact on victims, damage, and forecast of the impact of natural disasters in Indonesia for the period from 2021 through September 2025.

a. Total Disasters

The total disasters visualization summarizes the overall number of natural disaster events recorded in Indonesia during the observation period from January 2021 to September 2025. As shown in figure 9, the dashboard recorded 21,986 disaster events, providing an overview of disaster occurrence frequency throughout the study period. This indicator serves as the primary reference for assessing disaster activity before conducting more detailed analyses of disaster impacts across different dimensions.

TOTAL BENCANA**21,986**

Kejadian

Figure 9. Visualization of Total Disasters

The card visualization enables users to obtain essential disaster information quickly without reviewing extensive tabular reports. Integrating this indicator into the Business Intelligence dashboard improves situational awareness and facilitates rapid monitoring of disaster occurrences through an interactive analytical environment.

b. Total Casualties

The total casualties visualization presents the cumulative number of people affected by natural disasters, including fatalities, injuries, and missing persons. Based on the dashboard results, the total number of casualties reached 44,552 people, as presented in figure 10. This indicator summarizes the overall human impact of disasters during the study period and provides a comprehensive measure of disaster severity.

TOTAL KORBAN**44,552**

Meninggal + Terluka + Hilang

Figure 10. Visualization of Total Casualties

Presenting casualties as a key indicator enables stakeholders to rapidly assess the magnitude of disaster impacts on affected communities. Combined with the dashboard's interactive filtering capabilities, this visualization supports comparative analyses across provinces, disaster types, and time periods.

c. Fatalities

The fatalities visualization displays the total number of disaster-related deaths recorded during the observation period. As shown in figure 11, the dashboard indicates that 2,752 fatalities occurred as a result of natural disasters between January 2021 and September 2025. This indicator reflects one of the most critical measures of disaster severity because it represents the direct human consequences of disaster events.

KORBAN MENINGGAL**2,752**

Jiwa

Figure 11. Visualization of Fatalities

Monitoring fatalities separately from other casualty indicators enables decision-makers to evaluate disaster severity more effectively and supports the prioritization of mitigation, emergency response, and humanitarian assistance programs.

d. Total Damage

The total damage visualization summarizes the cumulative infrastructure damage caused by natural disasters, including damaged houses, flooded houses, and damaged public facilities. Based on the dashboard results shown in figure 12, the total recorded damage reached 5,905,009 units during the observation period. This key indicator provides an overall overview of disaster impacts on physical infrastructure across Indonesia.

TOTAL KERUSAKAN**5,905,009**Rumah Rusak + Terendam
+ Fasum Rusak**Figure 12.** Visualization of Total Damage

The visualization enables users to evaluate infrastructure losses efficiently and supports disaster management agencies in identifying the overall scale of physical damage. This information can assist in planning post-disaster recovery, infrastructure rehabilitation, and resource allocation.

e. Damaged Homes

The damaged homes visualization presents the total number of residential buildings affected by natural disasters. As illustrated in figure 13, a total of 410,698 houses were recorded as damaged during the study period. Housing damage represents one of the most significant indicators of disaster impacts because it directly affects the living conditions and well-being of affected communities.

RUMAH RUSAK**410,698**

Unit

Figure 13. Visualization of Damaged Homes

The visualization provides a concise overview of residential damage and supports authorities in estimating post-disaster housing recovery needs. Integrating this indicator into the Business Intelligence dashboard enables users to analyze housing damage alongside casualty and infrastructure indicators, thereby providing a more comprehensive assessment of disaster impacts.

f. Visualization of the Disaster Impact Distribution Map

The disaster impact distribution map was developed using tableau's geographic visualization capabilities to illustrate the spatial distribution of disaster impacts across Indonesian provinces. The dashboard includes the "Pilih Dampak" (Select Impact) parameter, allowing users to dynamically switch between casualty indicators and infrastructure damage indicators. This interactive functionality enables users to explore disaster impacts from different analytical perspectives without changing the dashboard layout.

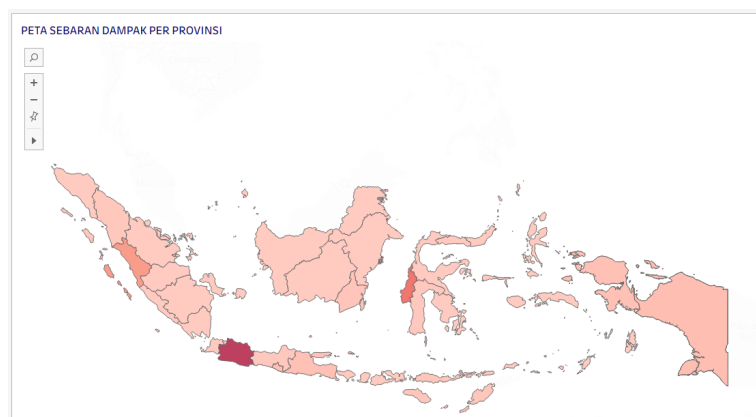


Figure 14. Visualization of a Map Based on Casualty Parameters

Based on the casualty parameter, figure 14 indicates that West Java recorded the highest absolute number of disaster casualties during the observation period. However, these values represent recorded disaster impacts contained in the BNPB dataset and should not be interpreted as a normalized measure of disaster risk because population size, geographical area, and exposure were not considered in this study. The interactive map assists decision-makers in identifying provinces with relatively higher recorded disaster impacts and supports regional disaster mitigation planning.

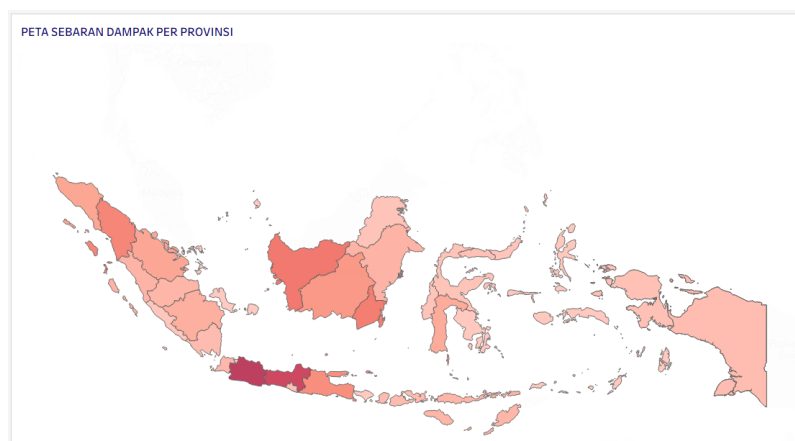


Figure 15. Visualization of a Map Based on Damage Parameters

Figure 15 presents the spatial distribution of disaster impacts based on infrastructure damage. The visualization shows that West Java recorded the highest level of damage, followed by several other provinces on Java Island, while many provinces in eastern Indonesia exhibited relatively lower recorded damage. The differences observed in the map demonstrate the uneven distribution of disaster impacts across Indonesia and highlight the usefulness of geographic visualization for identifying regional priorities in disaster recovery and infrastructure rehabilitation.

g. Graphical Visualization of the Top 10 Provinces with the Greatest Impact

The dashboard provides a bar chart visualization that ranks the ten provinces with the highest disaster impacts according to the selected impact parameter. This visualization enables users to compare disaster impacts among provinces and identify regions requiring greater attention in disaster management. Interactive filtering allows the ranking to be updated dynamically based on the selected disaster impact indicator.

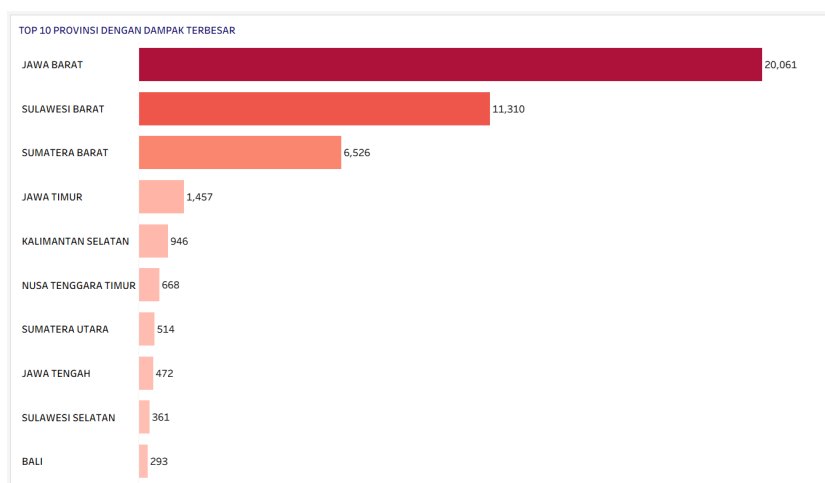


Figure 16. Visualization of a Bar Chart Based on the Casualty Parameters

As shown in figure 16, West Java recorded the highest number of casualties (20,061), followed by West Sulawesi (11,310) and West Sumatra (6,526). These findings indicate that recorded disaster casualties are concentrated in several provinces rather than being evenly distributed across Indonesia. The ranking visualization facilitates comparative regional analysis and assists policymakers in prioritizing disaster preparedness and emergency response programs in provinces with higher recorded disaster impacts.

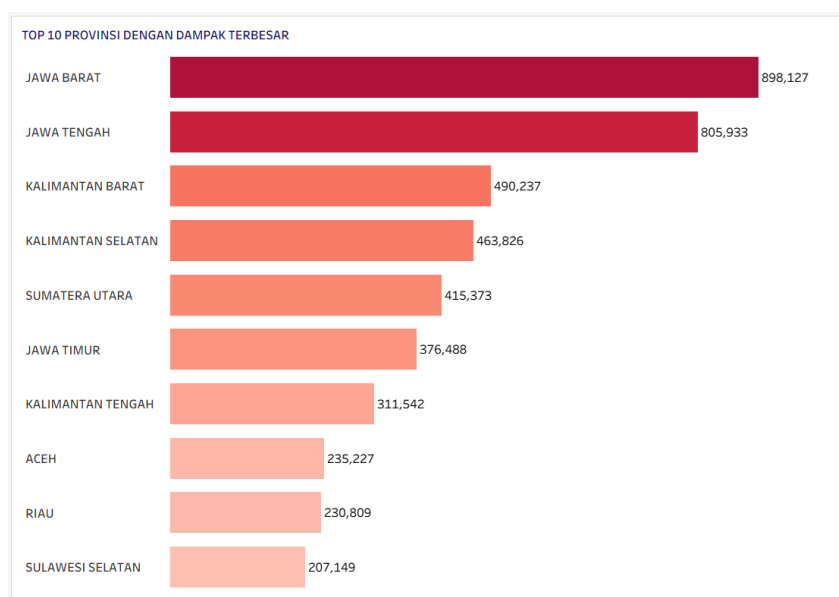


Figure 17. Visualization of a Bar Chart Based on the Damage Parameters

Figure 17 presents the ranking of provinces based on infrastructure damage. The results indicate that West Java experienced the highest recorded damage (898,127 units), followed by Central Java (805,933 units). These findings demonstrate that infrastructure damage varies considerably among provinces and tends to be concentrated in specific regions. Such comparative information supports more effective planning of post-disaster rehabilitation, reconstruction, and resource allocation.

h. Visualization of Casualty Impacts by Disaster Type

A stacked bar chart was developed to compare casualty impacts across different disaster types. The visualization includes three casualty indicators, namely fatalities, missing persons, and injuries, enabling users to evaluate the contribution of each disaster category to overall human impacts. The stacked visualization also provides a clearer representation of casualty composition among disaster types.

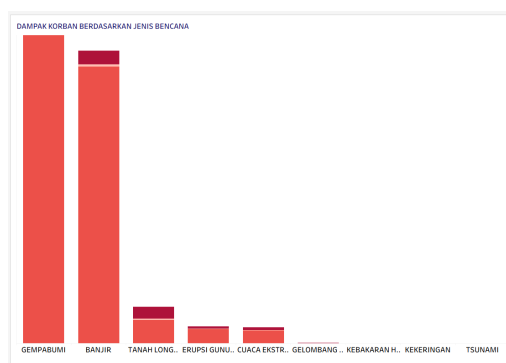


Figure 18. Visualization of a Stacked Bar Chart

Figure 18 shows that earthquakes and floods contributed the largest numbers of casualties compared with other disaster categories during the observation period. In contrast, disaster types such as tsunamis and droughts recorded relatively lower casualty impacts. This comparison demonstrates the usefulness of multidimensional visualization for identifying disaster categories that contribute most significantly to human losses and supports disaster preparedness planning by highlighting disaster types that require greater mitigation attention.

i. Visualization of Disaster Impact Trends and Predictions

Trend and forecast visualizations were developed to analyze historical disaster impacts and estimate short-term future trends using tableau's built-in forecasting functionality based on the Exponential Smoothing (ETS) model. The analysis was performed using monthly disaster impact data from January 2021 to September 2025, while the forecast covered the period from October 2025 to December 2026. The dashboard provides the "Pilih Dampak" (Select Impact) parameter, allowing users to dynamically switch between casualty and damage indicators. This interactive capability enables users to compare historical observations with projected trends within a single analytical environment and supports exploratory analysis for disaster preparedness and planning.

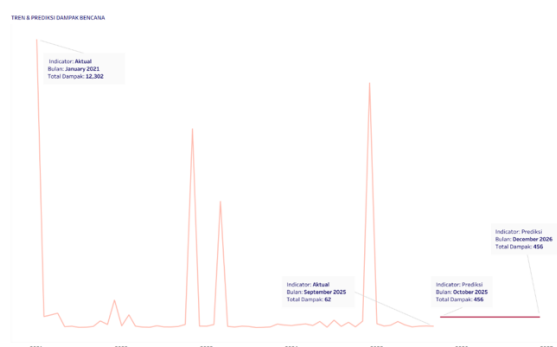


Figure 19. Visualization of Trends and Predictions Based on Casualty Parameters

Figure 19 presents the historical trend and forecast of disaster impacts based on the casualty parameter. The historical data indicate considerable monthly fluctuations in disaster casualties throughout the observation period. The highest recorded impact occurred in January 2021, with 12,302 casualties, whereas the latest observed value in September 2025 decreased to 62 casualties. Using tableau's built-in ETS forecasting model, the projected number of casualties remains relatively stable at approximately 456 casualties from October 2025 through December 2026. The relatively constant forecast suggests that, based on the available historical observations, the ETS model did not identify a strong increasing or decreasing trend during the forecast period.

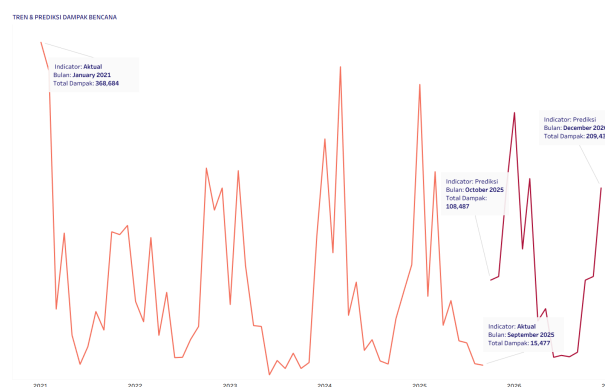


Figure 20. Visualization of Trends and Predictions Based on Damage Parameters

Figure 20 illustrates the historical trend and forecast based on the damage parameter. Similar to the casualty trend, the historical data show substantial monthly fluctuations in disaster damage between January 2021 and September 2025. The highest

recorded damage occurred in January 2021, reaching 368,684, while the latest observed value in September 2025 was 15,477. Based on the ETS forecasting model, the projected damage impact for October 2025 is 108,487, and the forecast continues to fluctuate, reaching 209,434 in December 2026. These results indicate that the model projects continued variability in disaster damage rather than a consistent upward or downward trend.

To evaluate the forecasting performance, tableau automatically generated several quality metrics, including Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Scaled Error (MASE), and Mean Absolute Percentage Error (MAPE), as summarized in table 4. These metrics were used to assess the performance of the ETS forecasting model based on the available historical observations.

Table 4. Forecast Performance Evaluation Using the ETS Forecasting Model

Parameter	ETS Model	RMSE	MAE	MASE	MAPE
Casualties	Additive	2,539	1,459	1.22	1,906.2%
Damage	Multiplicative	69,623	48,935	0.78	81.6%

The casualty forecast employed an additive ETS model, producing an RMSE of 2,539, an MAE of 1,459, a MASE of 1.22, and a MAPE of 1,906.2%. The very high MAPE indicates substantial variability in the casualty data, particularly because several observations contain relatively small values that increase percentage-based forecasting errors. Conversely, the damage forecast used a multiplicative ETS model, resulting in an RMSE of 69,623, an MAE of 48,935, a MASE of 0.78, and a MAPE of 81.6%. The MASE value below 1 suggests that the multiplicative ETS model performs better than a naïve forecasting benchmark for the damage series, although the MAPE indicates that forecasting errors remain relatively high. Therefore, the forecasting results should be interpreted as exploratory trend projections rather than definitive predictions, particularly because the historical dataset only covers observations up to September 2025. Despite these limitations, integrating the ETS forecasting model into the Business Intelligence dashboard extends its functionality beyond descriptive visualization by providing additional insights into potential future disaster impact trends and supporting evidence-based disaster preparedness and decision-making.

j. Business Intelligence Dashboard

The Business Intelligence dashboard integrates all analytical components into a single interactive platform for analyzing natural disaster impacts in Indonesia. As presented in figure 21, the dashboard combines cards visualization, geographic distribution maps, Top 10 province rankings, disaster impact analysis by disaster type, and trend forecasting. In addition, the dashboard provides interactive filtering based on year, disaster type, province, and the “Pilih Dampak” (Select Impact) parameter, enabling users to dynamically switch between casualty and damage indicators according to their analytical needs.



Figure 21. Business Intelligence Dashboard View

Figure 21 demonstrates that the proposed dashboard successfully transforms historical disaster records into an integrated analytical environment that supports multidimensional exploration. During the observation period, the dashboard recorded 21,986 disaster events, 44,552 casualties, 2,752 fatalities, 5,905,009 infrastructure damage records, and 410,698 damaged houses. The interactive map and Top 10 ranking indicate that West Java recorded the highest absolute disaster impacts based on the available BNPB dataset, while the disaster-type visualization shows that earthquakes and floods contributed substantially to overall disaster impacts. Furthermore, the forecasting component provides exploratory projections of future disaster impacts using tableau's built-in Exponential Smoothing (ETS) forecasting model, complementing historical trend analysis. The Business Intelligence dashboard developed in this study has been published on tableau Public and can be accessed via the following link: https://public.tableau.com/shared/MY647N6C6?:display_count=n&:origin=viz_share_link

Overall, the integration of a Kimball-based data warehouse, ETL processes, interactive visualization, and forecasting within a single dashboard enhances disaster data exploration beyond conventional tabular reporting. The proposed Business Intelligence dashboard enables decision-makers to analyze disaster impacts from temporal, geographical, disaster-type, casualty, and damage perspectives, thereby providing more comprehensive support for evidence-based disaster mitigation and response planning.

4. Conclusion

This study developed a Business Intelligence dashboard for analyzing natural disaster impacts in Indonesia by integrating a Kimball-based data warehouse, ETL processes using Pentaho Data Integration, interactive visualization in tableau, and the Exponential Smoothing (ETS) forecasting model. The proposed framework successfully transformed disaster records into an integrated analytical platform that supports multidimensional analysis based on time, location, disaster type, casualties, and infrastructure damage. In addition to descriptive analysis, the dashboard provides exploratory forecasting capabilities that enable users to identify potential short-term disaster impact trends.

This study has several limitations. The forecasting analysis was performed using monthly disaster data from January 2021 to September 2025, and the ETS forecasting model relied solely on historical observations without incorporating external factors that may influence disaster impacts. Therefore, the forecast results should be interpreted as exploratory trend projections rather than definitive predictions. Future research may incorporate additional explanatory variables, evaluate alternative forecasting models, and conduct user-based evaluations to assess the usability and practical effectiveness of the proposed dashboard.

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